An Intelligent and Optimal Resource Allocation Approach in Sensor Networks for Smart Agri-IoT

Tyagi , Sumarga Kumar Sah ; Mukherjee, Amrit; Pokhrel, Shiva Raj; Kant Hiran, Kamal

Published in:
I E E E Sensors Journal

DOI (link to publication from Publisher):
10.1109/JSEN.2020.3020889

Publication date:
2021

Document Version
Accepted author manuscript, peer reviewed version

An Intelligent and Optimal Resource Allocation Approach in Sensor Networks for Smart Agri-IoT

Sumarga Kumar Sah Tyagi*, Amrit Mukherjee*, Shiva Raj Pokhrel and Kamal Kant Hiran

***Abstract*— A Wireless Sensor Network (WSN) is of paramount importance in facilitating smart Agricultural Internet of Things (Agri-IoT). It connects numerous sensor nodes or devices to develop a robust framework for efficient and seamless communication with improved throughput for intelligent networking. Such enhancement has to be facilitated by an adequate and smart machine learning-based resource allocation approach. With the ensuing surge in the volume of devices being deployed from the smart Agri-IoT, applications such as intelligent irrigation, smart crop monitoring and smart fishery would be largely benefited. However, the existing resource allocation techniques would be inefficient for such anticipated energy-efficient networking. To this end, we develop a distributed artificial intelligence approach that applies efficient multi-agent learning over the WSN scenario for intelligent resource allocation. The approach is based on dynamic clustering which coupled tightly with the Back-Propagation Neural Network and empowered by the Particle Swarm Optimization (BPNN-PSO). We implement the overall framework using a Bayesian Neural Network, where the outputs from BPNN-PSO are supplied as weights to the underlying neuron layer. We observe that the cost function and energy consumption demonstrate a substantial improvement in terms of cooperative networking and efficient resource allocation. The approach is validated with simulations under realistic assumptions.**

***Index Terms*— Agriculture-IoT, Bayesian Neural Networks, Wireless Sensor Networks.**

I. Introduction

THE global population is predicted to touch 9.6 billion by 2050 that poses a big problem for the agriculture industry [1]. Despite usual challenges like extreme weather conditions, undesirable climate change, and its impact on farming, the ensuing demand for food has been increasingly intractable. We are supposed to satisfy these increasing demands; therefore, researchers have started investigating smart IoT technologies for Agriculture (Agri-IoT) [2]. Such technologies will enable the agriculture industry to improve productivity, starting from optimizing the use of fertilizer to increasing the efficiency of farming. Our objective for Agri-IoT is to develop a framework for monitoring the crop field with the help of sensors (for light, humidity, temperature, soil moisture, etc.) and orchestrating the irrigation system.

Wireless Sensor Network (WSN), an essential building-block for Agri-IoT [3], formulate a robust large-scale autonomous monitoring and control network by randomly deploying a large number of small sensor devices, also known as nodes, having communication and computing capabilities. All devices are connected through wireless channels to complete their tasks and learn cooperatively.

A high-level framework of a WSN-based Agri-IoT is depicted in Fig. 1, where numerous Sensor Nodes (SNs) are deployed for several aspects of agriculture, from cattle management to machinery operation. All the data from SNs are collected by the sink node through wireless data exchange links even with random spatial placements and considerable movements. The data is often transferred to the core network via different gateways such as a Base Transceiver Station (BTS) for further processing, data analysis, which, therefore, could potentially automate the entire Agri-IoT system. Such automation mechanism is further backed up by a cooperative communication setup and cluster formation between the nodes based on the application requirements. We develop such an intrinsic mechanism to implant human-level intelligence in the Agri-IoT.

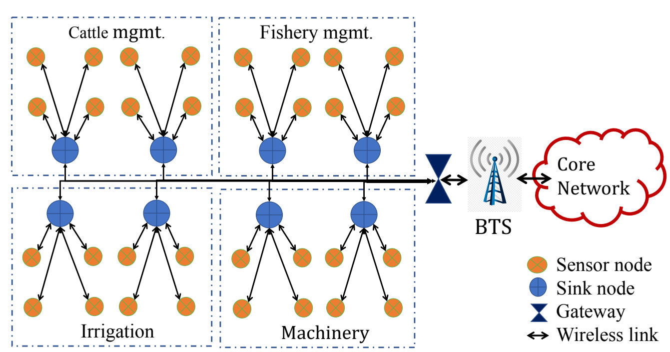

Fig. 1. An abstract view of the WSN framework for intelligent Agri-IoT

It is challenging to configure the nodes in the Agri-IoT to achieve effective allocation of resources such as network bandwidth and energy of the WSN [4]. Introduction of Distributed Artificial Intelligence (DAI) for distributed intelligent processing has already overcome the weakness of traditional centralized learning architecture. Therefore, based on Distributed

S. K. S. Tyagi with the School of Electronic and Information Engineering, Zhongyuan University of Technology, Zhengzhou, China. e-mail: (sumarga@zut.edu.cn).
A. Mukherjee is with Anhui University, Anhui, China. e-mail: (amrit140@ieee.org).
S. R. Pokhrel is with Deakin University, Melbourne, Australia, e-mail: (shiva.pokhrel@deakin.edu.au).
K. K. Hiran is with Aalborg University, Copenhagen, Denmark e-mail: (kkh@cmi.aau.dk).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSEN.2020.3020889, IEEE Sensors Journal

Problem Solving (DPS) approach, we propose a Multi-Agent System (MAS) to exploit the intelligence and flexibility. The new MAS, structurally alike usual WSN, approach investigates intelligence in the behaviour coordination and collaborative works among multiple agents [5]. In the proposed model, the multiple sensors have acted as multi-agents, and thus the DPS for DAI approach has been used to enhance the cooperative networking idea.

To solve the problem of efficient node allocation for WSN in Agri-IoT and realize optimal resource allocation with low energy consumption and low complexity, the WSN based on DAI is to be analyzed and studied theoretically. We first formulate a resource allocation model of WSN based on multi-agents. After that, we formulate an optimization problem for the process of resource allocation; the proposed Back Propagation Neural Network (BPNN) in the neural network has been adopted to develop an objective function and find an optimal resource allocation scheme.

The concept of the clustering [6]–[8] is described as similar objects that satisfy the objective function can be grouped into a cluster, and the objects between different clusters are supposed to be very different. Based on it, our approach divides the resource allocation process into two phases: inter-cluster formation followed by an intra-cluster formation. Based on the network status of the cluster, the Cluster Head (CH) is elected among the clusters that facilitate the allocation of the corresponding resources. The CH allocation to the resources shall be performed first, followed by a self-assessment, and comparing whether the current energy is higher than the target energy threshold. This identifies whether it is the task to be processed or the next stage of resource allocation is to be performed.

Considering limited energy as well as life cycle of the nodes in a cluster, the distance between nodes and energy consumption are defined using fitness functions. More specifically, two neural network-based optimization algorithms are used to optimize resource allocation, which will finally discover the optimal node configuration solution. For this, we establish a resource allocation model of WSN based on DAI. The optimized conditions are the configuration of sensor nodes and the node coverage, which are defined as the fitness function. The novelty of the proposed model lies in the implementation of Bayesian Neural Network (BNN) in BPNN for Agri-IoT applications. The existing works on IoT and WSN mainly focus on networking and computations using different optimization techniques.

The organization of this paper is as follows. The next section shows the related work of resource allocation in WSNs. Sections III and IV provide mathematical analysis of resource allocation based on DAI and the resource allocation between clusters, respectively. We discuss the optimization of resource allocation within clusters based on BPNN in Section V. Section VI shows the simulation and analysis. The last section concludes the paper with future scope.

II. Related works

There are many research results on resource allocation methods in WSN. Introduction of clustering can effectively reduce energy consumption of the system as well as balance the network-load. Authors in [7] used simple artificial fish school and ant colony algorithm for resource allocation of WSNs, and also optimized the clustering process. Authors in [9], [10] also used clustering to improve the LEACH-CS algorithm and proposed a low-energy adaptive clustering resource allocation protocol, which is based on market mechanism. The market mechanism scheme aimed at maximizing profit to realize distributed resource allocation through the negotiation and adjustment of agents.

Considering the QoS, authors have adopted a centralized resource allocation method in [11], [12] to minimize the allocated energy consumption. In [13], a resource allocation model based on a queuing network was established. The steady-state analysis of the model was used to find an optimal resource allocation scheme. These methods mainly consider issue from the perspective of reducing network energy consumption. However, as the number of users grow that demands different QoS requirements of different users. Therefore, a more dynamic and efficient resource allocation mechanism needs to be established. To maximize utilization of resources, authors scheduled the tasks reasonably according to the QoS of different users to allocate them to different nodes in [14]. In the face of the heterogeneity of WSN, reference [15] adopts the resource allocation method based on heterogeneous statistical QoS to transform the target into the maximization of network throughput. Some researchers use intelligent algorithms to optimize the performance of resource allocation.

In [16], Genetic Algorithm (GA) is used to optimize the configuration of sensor nodes, where the node coverage is defined as fitness function. The fitness function constitutes task transmission time and energy consumption. A resource allocation algorithm based on Binary Particle Swarm Optimization (BPSO) is adopted in [14] to optimize the node configuration and resource scheduling of WSNs. To verify the feasibility of the scheme, different topological structures and transfer functions are analyzed and discussed. In [17], the author used neural network to improve BPSO to optimize the resource allocation process of WSNs and significantly ameliorate the convergence speed. Considering an actual WSNs working environment is real-time and dynamic. Authors in [18] proposed an agent-based WSN resource allocation framework. Because the agent is responsible for data collection, fusion and distribution in the network, an accurate location information and response time of the agent will affect the delay and work efficiency of the entire network [19]. Reference [20] adopted an agent-based Fuzzy Group Optimization algorithm (FGO) to reduce energy consumption and prolonged the life cycle of nodes in the WSNs. In [21], authors reduce the number of sensors to be selected using Multiplayer Perceptron (MLP), Support Vector Machine (SVM) and Naïve Bayes for extending WSN lifetime.

The literature survey briefs existing AI-driven models, and hence provides a motivation to propose an energy-efficient networking model using BNN in IoT applications as discussed in later sections.

III. Mathematical analysis of BPNN-APSO and BNN

For the convenience of readers, all the mathematical notations used in this paper are summarized in Table I.

TABLE I
NOTATION TABLE

Symbol	Description	Symbol	Description
t	Time	π	Initial agent
P	Power consumption	E	Environment space
$U(t)$	Memory usage in time t	β_a^π	Target value
Cf	Cost function	X	Input of BPNN
ϕ_i	Tasks to be executed	Y	Output of BPNN
λ_j^i	Task variable	L	No. of layers
$QoS_{\lambda_j^i}$	Targeted QoS value	w_{ij}	Weight values
AE	Auto-correlation Error	m	No. of sets
ED	Euclidean distance	l	No. of set length
l	No. of sensing channels	n	Cluster size
θ	Energy threshold		
$\bar{r}_{m+l}$	Predicted value set	F	Fitness function
V	Space set of particles	C	Global fitness
ϵ	Global extremum	ω'	Weighting coefficients
pb_i	Extremum at initial	$r1, r2$	Random functions
gb_d	Extremum at final	$c1, c2$	Acceleration constants

According to the technical requirements of Agri-IoT, we must ensure the QoS of the system is satisfied. Due to the limited resources of sensor nodes and to improve the network life cycle, two constraints should be considered simultaneously, these are, power consumption of node batteries and the use of memory. When the current time is t, the node battery power consumption of the system is expressed as:

$$P(t) = P(t-1) - P_{(MA-DA)} - P_{DA}PN(t-1) \quad (1)$$

where, $P_{(MA-DA)}$ is the power consumed when Manager Agent (MA) communicates with Deliberative Agent (DA). P_{DA} is the power consumed when choosing an appropriate CH as DA. In $t \leq 1$ time, PN is the power consumed by the next resource allocation, which is closely related to the location information of the selected CH. Similarly, the expression for the memory usage of the system in time t is:

$$U(t) = U(t-1) - P_{(MA-DA)} - P_{DA}PN(t-1) + P_{DA}PN(t-2) \quad (2)$$

Based on the above discussion, a cost function of the system can be constructed as:

$$Cf = \sum_{i=1}^{j} \phi_i \mu T QoS_{\lambda_j^i}[P(t)_i + U(t)_i] \quad (3)$$

where, $\phi_i = \lambda_1^1, \lambda_2^1, ..., \lambda_j^i$ is a task to be executed in the system, and λ_j^i is a task variable. $QoS_{\lambda_j^i}$ is the targeted QoS value to be met when executing the task.

According to reference [22], an agent is represented by a function π, and the agent is distributed in an environment space E. To measure a relationship between the agents, the Kolmogorov complexity is introduced to indicate the information measure, expressed as:

$$\psi(\pi) = \sum_{a \in E} 2^{-K(a)} \beta_a^\pi \quad (4)$$

where $2^{-K(a)}$ is the complexity loss value, $\sum_{a\in E}$ is the sum of activities in different environment spaces, and β_a^π is the target value we want to achieve.

In this paper, DAI is used to calculate the optimal resource allocation in the interaction between MA and Coordinator Agent (CoA) in real-time. One may use the Power Spectral Density (PSD) of the received signal to predict the position allocation information of all MA. The AE is auto-correlation error and ED is Euclidean distance.

$$\frac{AE}{\frac{1}{T}[p^{\frac{g^2-2}{2}}]\sum_{l=1}^{p} a_l(T)} = \frac{ED}{2}\sum_{l=2}^{p} a_l(T) \quad (5)$$

$$where,\ \sum_{l=2}^{p} a_l(T) \in \sum_{l=1}^{p} a_l(T)$$

To make the resource allocation scheme more reasonable, we have to calculate all possible spatial location allocations of the MA.

$$a = a_1(T)\sum_{l=2}^{p} a_l(T) = \lambda(\pi) = \sum_{l=2}^{p} 2^{-K(a)}\beta_a^\pi \quad (6)$$

$$where,\ \sum_{l=2}^{p} a_l(T) \in \sum_{l=1}^{p} a_l(T)$$

At this time, all the spatial position assignments of MA will form a real-time continuous prediction, which can be expressed by mathematical analysis as:

$$\frac{AE}{\frac{1}{T}[p \cdot \frac{g^2-2}{2}]} = \frac{ED}{2}\sum_{l=2}^{p} a_l(T)\sum_{l=1}^{p} a_l(T) \quad (7)$$

$$\frac{AE}{\frac{1}{T}[p \cdot \frac{g^2-2}{2}]} = \frac{ED \cdot a}{2}\sum_{l=2} 2^{-K(a)}\beta_a^\pi \quad (8)$$

In the system, each node must communicate with at least two nodes, so the net gain is much larger than a single sensor network. When the number of channels is $p > 2$, $\frac{1}{T}[p \cdot \frac{g^2}{2} - 1] \rightarrow 1$. DAI use the test data of AE to obtain the position information of the sensor node positioning, and obtain the position and distance response relationship between MA and CoA as:

$$ED = \frac{1}{T}\sum_{l=1} 2^{-K[a_l(T)]}\beta_a^\pi \quad (9)$$

After accepting the resources allocated by MA, DA will conduct a self-assessment of its energy. We set a threshold θ in advance, and the evaluation rules are as follows:

$$\begin{cases} \theta_{DA} > \theta,\ intra-cluster\ allocation\ based\ on\ NN. \\ \theta_{DA} \leq \theta,\ DA\ directly\ performs\ the\ task. \end{cases} \quad (10)$$

Only when the energy of the DA exceeds the threshold, the DA will perform the task assigned by the MA, otherwise, it will enter the second stage of resource allocation, that is, the resource allocation process in the cluster. We will use two neural network methods to find the best resource allocation scheme.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSEN.2020.3020889, IEEE Sensors Journal

IV. Optimized resource allocation scheme in intra-cluster based on PSO-BPNN

To realize the optimal resource allocation in the system cluster and improve the life cycle of the network, we will optimize the set objective function in this section. Neural networks have been proved to be effective in approximating the required accuracy of measurement functions [14], however, BPNN is widely used in practice. We will use the neural network to estimate the objective function and find the best resource allocation strategy. In our implementation, BPNN is composed of a three-layer network structure, which has a function of error feedback, and has slow convergence issue. Therefore, we adopt Particle Swarm Optimization (PSO) algorithm to improve the learning speed of BPNN. The details of implementation process is illustrated in Fig. 2.

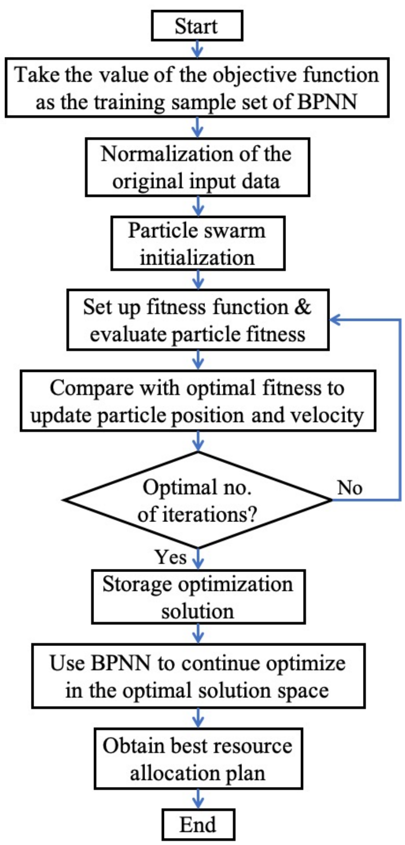

Fig. 2. Flow chart of resource allocation optimization based on PSO-BPNN

The flow chart depicted in Fig. 2 is described as follows:
step 1- The training sample set of BPNN is initiated based on objective functions that are sensed by the heterogeneous nodes, node number and their spatial deployment. The process starts at $t = 0ms$ during the training of the sample data with respect to their initial movements.
step 2- Based on the training sample set of BPNN, the original data is then normalized. The normalization process is used for standardizing mathematical modeling of the method along with other parametric conditions.
step 3- The model now implements Particle Swarm initialization using the normalized data mapped on to training sample data of the objective function. This serves as the pre-optimization phase, where the data are generated based on dynamic clustering and normalized accordingly.
step 4- Here, the model is creating a fitness function based on the normalized and trained objective and cost functions. This step will behave as the initial optimization phase which carries further the objective functions based on the BPNN outputs.
step 5- In this stage, based on the previous fitness function outputs, the optimal fitness function is classified to update the particle position and velocity noted from the spatially distributed nodes.
step 6- This is the foremost step of the proposed model, where the optimal number of iterations is calculated based on the BPNN-PSO approach. If the optimal number of iterations is not reached, particle fitness is again calculated and proceed for optimization.
step 7- As soon as the optimal number of iterations is achieved during cooperative communication among the Agri-IoT nodes, the data storage for iterative computations come into the picture, which enables preparing the new training set for the next time instance.
step 8- As soon as the storage optimization takes place during dynamic clustering, the BPNN cost functions are updated and corresponding optimal fitness functions are derived. Based on this cycle, the best resource allocation plan is continuously updated and implemented with respect to time.

The training process of BPNN is divided into two parts: forward transmission and reverse feedback. The original data of the node position and energy load obtained in the previous section are normalized, and the obtained data set is used as input, which is then composed with the target output set Training set to train BPNN. The work of forward transmission is to output the input set as the predicted target set. The input layer of BPNN contains several input units. In addition to the input layer, the other layers contain several calculation units. The input value X and output value Y of each layer node are as follows:

$$X_i^L = \sum_j Y_j^{L-1} w_{ij}^L + \theta_i^L \tag{11}$$

$$Y_i^L = \frac{1 - exp(-X_i^L)}{1 + exp(-X_i^L)} \tag{12}$$

where L represents the number of layers, w_{ij} is the weight value of the node connection between the adjacent layers, and θ_i represents the threshold of the node.

If the input is m sets of length l, set to $R_m = r_m, r_{m+1}, ..., r_{m+l-2}, r_{m+l-1}$, the corresponding target output is r_{m+l}. The predicted value we set is $\bar{r}_{m+l}$, and the mean variance D is:

$$D = \left(\sum d_m^2\right)/2 \tag{13}$$

$$d_m = \bar{r}_{m+l} - r_{m+l} \tag{14}$$

In order to improve the accuracy of prediction, reverse feedback is needed to reduce the mean square error. According to the updating formulas of w and θ. Here, w of BPNN constantly updated by D, the updating formulas are as follows:

$$w_m = w_{m+1} + \Delta w_t \tag{15}$$

$$\Delta w_m = -\zeta \frac{\partial D}{\partial w_m} + \beta \Delta w_{t-1} \tag{16}$$

The updated formula for w is:

$$\theta_m = \theta_{m-1} + \Delta \theta_t \tag{17}$$

$$\Delta \theta_m = -\zeta \frac{\partial D}{\partial \theta_m} + \beta \Delta \theta_{t-1} \tag{18}$$

The initial weight and threshold of BPNN are optimized by using the global search of PSO. According to reference [23], the mathematical model of PSO is as follows:

$$U_{PSO} = (n, t, V, X, F, C) \tag{19}$$

where, n is the cluster size. Also, $V = (V_{i1}, V_{i2}, ..., V_{iN})$ represents the space set of particle flying speed, $X = (X_{i1}, X_{i2}, ..., X_{iN})$ represents the position space of particles in the search space, F is the fitness of the mapping process, and C is the aggregation degree of the particle swarm. During the iterative process, the particles will dynamically update their positions and velocities based on the individual extremum pb_i and the extremum gb_d of the entire particle swarm.

$$\begin{aligned} V_{ij}(t+1) = \omega' V_{ij}(t) + c_1 * r_1(t)[pb_{ij}(t) - X_{ij}(t)] \\ + c_2 * r_2(t)[gb_{id}(t) - X_{ij}(t)] \end{aligned} \tag{20}$$

$$X_{ij}(t+1) = X_{ij}(t) + V_{ij}(t+1) \tag{21}$$

where, c_1 and c_2 are the acceleration constants, r_1 and r_2 are two random functions that take value between $[0, 1]$. Each vector of particles in PSO is used as the connection weight of BPNN to continuously optimize the initial weight of BPNN. There are M different weighting coefficients ω' in particle swarm, and this value varies with pb_i and gb_d.

Different weighting coefficients will form different optimal solution spaces, and then use BPNN to continue to optimize in the optimal solution space, and finally obtain the best resource allocation scheme. The position vector of the particle is an integer. Each entity of the vector represents an allocation scheme depending on the number of tasks and the number of nodes in the Task Agent (TA). When the number of tasks is 5 and the number of TA nodes is 3, the resource allocation matrix can be written as follows:

$$P = \begin{bmatrix} 0 & 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \end{bmatrix} \tag{22}$$

Here, F is determined by the global extremum ε and the average of a single extreme value $\Delta\varepsilon_{ave}$, and its range is $(0, 1]$.

$$\varepsilon_t = f(pb^t) \tag{23}$$

$$\varepsilon_{ave,i}^t = \left(\sum_{i=1}^{n} \varepsilon_t \right) / n \tag{24}$$

$$F = o_1 \frac{min(\varepsilon_t, \varepsilon_{t-1})}{max(\varepsilon_t, \varepsilon_{t-1})} + o_2 \frac{min(\Delta\varepsilon_{ave,i}^t, \varepsilon_{ave,i}^{t-1})}{max(\Delta\varepsilon_{ave,i}^t, \varepsilon_{ave,i}^{t-1})} \tag{25}$$

We can determine the optimal solution by comparing the ε of different iterations, and use ε_{ave} to obtain the changing trend of PSO.

Here, C is determined by the global fitness $\Delta\varepsilon_{ave,i}^t$ and $\Delta\varepsilon_d^t$.

$$\varepsilon_d^t = \left(\sum_{i=1}^{n} f(X_i^t) \right) / n \tag{26}$$

$$C = \frac{min(\Delta\varepsilon_{ave,i}^t, \delta\varepsilon_d^t)}{max(\Delta\varepsilon_{ave,i}^t, \delta\varepsilon_d^t)} \tag{27}$$

In the above formula, by comparing $\varepsilon_{ave,i}^t$ and ε_d^t), we can determine whether all particles are aggregated to the best value. Then, according to F and C, dynamic update formula of the weighted coefficient is as follows:

$$\begin{aligned} \omega' = \omega_e F + \omega_a C, F \in (0, 1],\ C \in [0, 1], \\ \omega_f - \omega_e < \omega' < \omega_f + \omega_a \end{aligned} \tag{28}$$

The proposed BPNN traning method is briefly described as follow:

Algorithm 1: Training of BPNN for resource allocation

Input : X, Y 1*1 matrix
Output: X, Y 1*1 matrix

for $i = 1$ *to* l **do**
  for $j = 1$ *to* l **do**
    C[i,j] = 1;
  end
end
while *C[i,j]* $\leq \omega_i^l (i = 1, 2, ..., k)$ **do**
  η = $\omega[i, j]$;
  loop from 1 to k;
  for $b_i^l \leq 1$ **do**
    m = m[i]+1;
    for $l = 1$ *to* m **do**
      $\omega' = \omega_e F + \omega_a C$;
    end
  end
  $\eta = \eta - 1$;
end

The simulation and results section will thoroughly discuss the energy consumption and QoS of the system. Also, the life of the whole system model as to a certain extent it depends on the energy consumption.

V. Simulations and results

The proposed work is validated with two different simulation scenarios. One is regarded as small scale scenario, and the other one is large scale scenario. In the small scale scenario, the area coverage by the nodes = 100m X 100m, number of nodes = 1000, whereas, for the large scale scenario, the area coverage by the nodes = 500m X 500m; number of nodes = 10000. For both scenarios, simulation time = 1000ms; nodes are distributed initially as per poisons distribution; minimum and maximum signal to noise ratio = 2 to 20 dB; hidden

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSEN.2020.3020889, IEEE Sensors Journal

BNN layers = 10 and dynamic clustering for general WSN applications.

To assess the proposed resource allocation using BNN approach for Agri-IoT, we have calculated the clustering rates, energy consumption profiles, simulation time, and transitions between input layer and output layer, for three different comparing schemes DAI, HML and APSO. Moreover, the cooperative communication is validated using error rate plot to support the model. Those metrics will not only justify the computation speed but also the energy-efficiency of the proposed method.

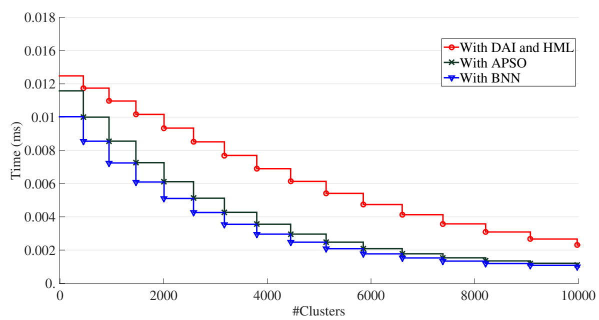

Fig. 3. Clustering rates for different schemes (Small scale scenario).

The Fig. 3 depicts clustering rates (number of clusters formation per unit time) of all the comparing schemes for small scale scenario. Clustering rate signifies how fast numbers of clusters can be formed to accommodate network load in the IoT. As we increase the dynamic clustering among the Agri-iot nodes, the overall cooperative communication becomes efficient due to continuous BPNN and PSO. This will result in decrease the energy consumption in par with the system response, and hence increase the resource allocation in an efficient manner. It means the resource allocation is as efficient as the clustering rate is higher. The proposed method have highest clustering rate that can be noticed from the Fig. 3. The proposed method achieves 44% and 65% higher clustering rate than APSO and DAI & HML, respectively.

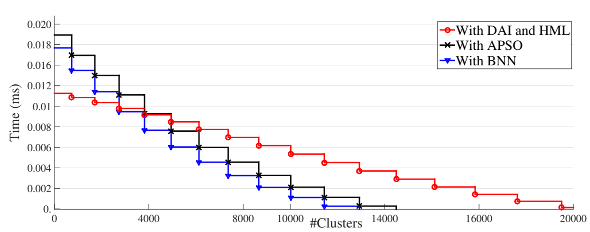

Fig. 4. Clustering rates for different schemes (Large scale scenario).

Similarly, the proposed method is checked for the large scale scenario, and the corresponding graph is plotted in Fig. 4. The figure shows that our proposed method has achieved 50% and 73% higher clustering rate than APSO and DAI & HML, respectively. Therefore, with validation for both scenarios, the proposed method could most efficiently allocate network resources in the WSN-based Agri-IoT than other comparing schemes.

It is not only paramount importance for resource allocation but also for significantly lowers the energy consumption that will be discussed in the following paragraph.

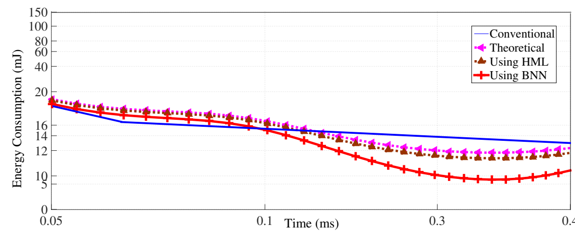

Fig. 5. Energy consumption profiles for small scale scenario.

Energy consumption profiles for all three schemes are plotted in the Fig. 5 considering small scale scenario. The simulation time is varied and the change of the energy consumption is observed. Initially, the energy consumption decrease but at later stages it slightly increases due to dynamic formation of the clusters. If the number of clusters are fixed in any network, then the energy consumption will be reduced. The Fig. 5 shows that the BNN performs a substantial improved energy consumption as compared to the traditional methods. That means the proposed method could save 49%, 36%, and 31.6% more energy than conventional, theoretical, and HML methods, respectively.

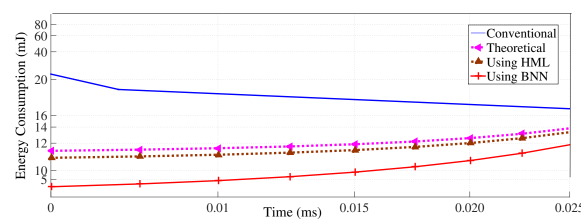

Fig. 6. Energy consumption profiles for large scale scenario.

Similarly, for a massive scale deployment deployment of sensors, the energy consumption profiles for different schemes are depicted in Fig. 6. Where, the graph of all the schemes, except the conventional, dynamically varying energy consumption commensurate with the formation of number of clusters. As we increase the number of nodes, more than 1000, the proposed model shows optimum results and consumes less energy as compared to the other existing methods and conventional method. This is due to feedback in BNN and continuous optimization in the Agri-IoT network during cooperative communication networking. Most importantly, our proposed method always consume less energy than other schemes. Thus, in both the scenarios, the proposed method substantially consume less energy comparing with the other schemes.

This significant energy saving scheme is very important for any large scale IoT applications such as Agri-IoT, where thousands of nodes are interconnected and consume energies at different levels of stack in the network.

As shown in Fig. 7, the cost function variation in accordance to normalized transition time from CH and I-O layer variations

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSEN.2020.3020889, IEEE Sensors Journal

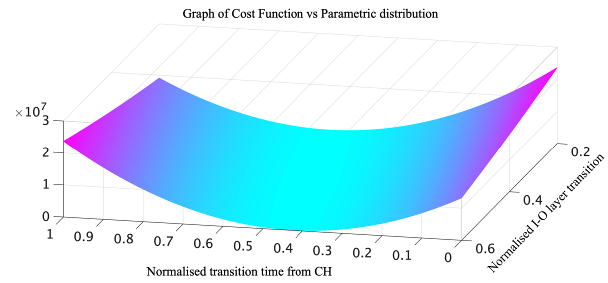

Fig. 7. Time response variation in clusters during resource allocation.

are presented. As it can be seen, initially at beginning, i.e. the first input layer of BNN, and the beginning of 1^{st} CH selection during dynamic clustering, the cost function is maximum. While, at the middle of I-I transitions, when the dynamic clustering is ongoing and 50% of the CH are identified the cost function is minimum. This is due to BPNN based PSO is continuous for global search for the optimum node positions. And at the later stages, the cost function is high which reveals a good quality of service for the proposed model after completion of dynamic clustering and the model reached the final output stage of BNN.

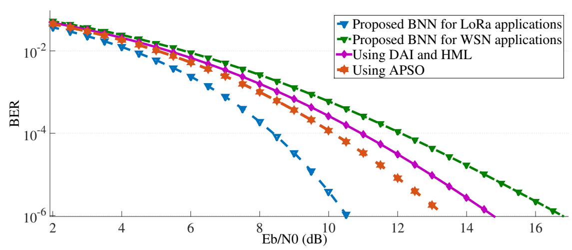

Fig. 8. Performance comparisons of different networks for small scale.

As illustrated in Fig. 8, the network performance is shown in terms of comparisons for Bit Error Rates (BER) during the overall networking using the proposed model and other existing models for small scale scenario. The simulations are performed for Low Range IoT applications (LoRa) and other general WSN based IoT applications, where the signal-to-noise ratio is maintained at the maximum of 20 dB.

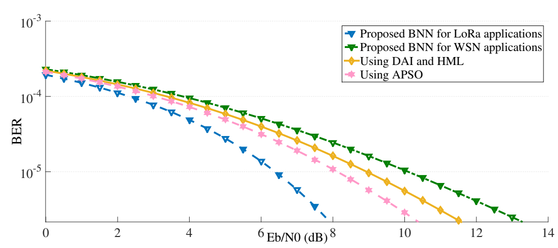

Fig. 9. Performance comparisons of different networks for large scale

Fig. 9, shows the BER performance for the large scale scenario, where the new BER is improved and the error rate is significantly decreased in from 6-12dB SNR which is an optimum condition for any IoT applications. Although we are increasing the number of nodes, the BNN processes the objective function and reduces the energy consumption with optimum time response, results in improved BER. As we know, the cooperative communication needs to be energy efficient in heterogeneous and dynamic clustering, reducing the BER for higher number of nodes in a large area justifies the proposed method.

The results presented for both the scenarios in comparison with existing DAI, HML and APSO methods, which are basically used for Cognitive Radio Sensor Network (CRSN) and WSN application. It can be clearly seen, as we increase the SNR, the BER is reduced in all the cases, but the BPNN proves to a better solution for Agri-iot applications which is basically a low SNR application. The simulation results are carried out using error function calculation for all the methods. It can be observed, the BER for performance with the proposed model illustrates a substantial improved performance as compared with DAI, HML and APSO techniques which are used for IoT dynamic clustering. This is due to BPNN based APSO and BNN theoretical model, which not only improves the energy consumption but also the overall networking performance that is the most essential for a smart Agri-IoT applications. A further advanced approach for security and privacy-aware collaborative learning across multiple WSNs for future Agri-IoT requires further investigations by using new technology such as Blockchain and federated learning along the lines of that of [24], which is left for future work.

VI. Conclusion and Future Directions

We proposed an energy-efficient resource allocation model using a neural network approach for WSN-based smart Agri-IoT framework. Initially, our model uses BPNN and APSO for dynamic clustering and optimization of the cluster size. The BNN is implemented in each layer from input to output based on the selection of the cluster from the previous stages. This enhances not only the overall dynamic clustering process, but also the BNN takes care of the computation time and energy consumption. For simulations, we have assumed the real-time parameters and environmental conditions for two different scenarios of Agri-IoT application, these are small scale scenario and large scale scenario. The significant difference between these two scenarios is considered: several nodes and the corresponding coverage areas. The simulated results are presented and compared with other existing methods to benchmark the performance. The work has been extended for large scale deployments by assuming micro-cell zones for IoT applications and Industrial IoT based WSN models.

References

[1] United Nations Food and Agriculture Organizarion, "How to Feed the World in 2050". http://www.fao.org/fileadmin/templates/wsfs/docs/expert/_paper/How_to_Feed_the_World_in_2050.pdf

[2] O. Elijah, T. A. Rahman, I. Orikumhi, C. Y. Leow and M. N. Hindia, "An Overview of Internet of Things (IoT) and Data Analytics in Agriculture: Benefits and Challenges," in IEEE Internet of Things Journal, vol. 5, no. 5, pp. 3758-3773, Oct. 2018.

[3] N. Ahmed, D. De and I. Hussain, "Internet of Things (IoT) for Smart Precision Agriculture and Farming in Rural Areas," in IEEE Internet of Things Journal, vol. 5, no. 6, pp. 4890-4899, Dec. 2018.

[4] H. P. Gupta, P. K. Tyagi and M. P. Singh, "Regular Node Deployment for k -Coverage in m -Connected Wireless Networks," in IEEE Sensors Journal, vol. 15, no. 12, pp. 7126-7134, Dec. 2015.

[5] M. G. Kibria, K. Nguyen, and G. P. Villardi, et. al, "Big Data Analytics, Machine Learning, and Artificial Intelligence in Next-Generation Wireless Networks," IEEE Access, vol. 6, pp. 32328-32338, 2018.

[6] H. P. Gupta, S. V. Rao, A. K. Yadav and T. Dutta, "Geographic Routing in Clustered Wireless Sensor Networks Among Obstacles," in IEEE Sensors Journal, vol. 15, no. 5, pp. 2984-2992, May 2015.

[7] Xiao H, Zhao X, Ogai H. "A New Clustering Routing Algorithm for WSN based on Brief Artificial Fish-School Optimization and Ant Colony Optimization", IEEJ Transactions on Electronics, Information and Systems, 2013, Volume 133, Issue 7, Pages 1339-1349.

[8] Sah Tyagi, S.K., Zhou, Y., Lin, T. et al. "Realization of a computational efficient BBU cluster for cloud RAN". J Ambient Intelligence and Humanized Computing (2018).

[9] Zimmerman A T, Lynch J P, Ferrese F T. "Market-based resource allocation for distributed data processing in wireless sensor networks," ACM Transactions on Embedded Computing Systems, vol. 12, no.3, pp. 1-28, 2013.

[10] S. R. Pokhrel, S. Verma, S. Garg, A. K. Sharma and J. Choi, "An Efficient Clustering Framework for Massive Sensor Networking in Industrial IoT," IEEE Transactions on Industrial Informatics (2020).

[11] P. Goswami, et.al., "An Energy Efficient Clustering using Firefly and HML for Optical Wireless Sensor Network," Optik, vol. 182, pp. 181-185, 2019.

[12] S. K. Sah Tyagi, T. Lin and Y. Zhou, "Thermal-Aware Dynamic Computing Resource Allocation for BBU Pool in Centralized Radio Access Networks," 2017 IEEE 85th Vehicular Technology Conference (VTC Spring), Sydney, NSW, 2017, pp. 1-5, doi: 10.1109/VTCSpring.2017.8108488.

[13] Victor Cionca , Ramona Marfievici , Roland Katona , Dirk Pesch . "JudiShare: Judicious resource allocation for QoS-based services in shared wireless sensor networks," in Proc. 2018 IEEE Wireless Communications and Networking Conference (WCNC), IEEE, 2018.

[14] A. Mukherjee, P. Goswami, Z. Yan, L. Yang and J. J. P. C. Rodrigues, "ADAI and Adaptive PSO-Based Resource Allocation for Wireless Sensor Networks," in IEEE Access, vol. 7, pp. 131163-131171, 2019.

[15] Martins F V C , Carrano E G , Wanner E F , et al. "On a Vector Space Representation in Genetic Algorithms for Sensor Scheduling in Wireless Sensor Networks," Evolutionary Computation, vol. 22, no. 3, pp. 361–403, 2014.

[16] Wenzhong Guo , Jie Li ; Guolong Chen , Yuzhen Niu , Chengyu Chen. "A PSO-Optimized Real-Time Fault-Tolerant Task Allocation Algorithm in Wireless Sensor Networks," IEEE Transactions on Parallel and Distributed Systems, vol. 26, no. 12, pp. 3236 - 3249, 2014.

[17] K. Anusha , G.I. Shamini . "Power and resource allocation using modified binary particle swarm optimization in neural network," in Proc. 2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), IEEE, 2016.

[18] Fukuda H , Leger P. "An efficient agent location management for wireless sensor networks", in Proc. International Conference on Distributed Computing in Sensor Systems, IEEE, 2015.

[19] Guoying C , Yan W . "Multi-mobile Agent collaborative control data separation method in wireless sensor network," Journal of Computer Applications, vol.34, no.4, pp.910-915, 2015.

[20] Amrit Mukherjee, et.al., "Distributed Artificial Intelligence based Cluster Head power allocation in Cognitive Radio Sensor Networks", IEEE Sensor Letters, pp.1-4, 2019.

[21] Abdulaziz Y. B., Ismail M. K., "Energy management in wireless sensor networks based on Naive Bayes, MLP, and SVM Classifications: A comparative study", Journal of Sensors, Hindawi vol. 2016, Pages: 1-12, 2016.

[22] Legg S, Hutter M. "Universal Intelligence: A Definition of Machine Intelligence", Minds & Machines, vol.17, no.4, pp.391-444, 2007.

[23] Ziwei Y, et al., "Energy-efficient node positioning in optical wireless sensor networks", Optik, vol.179, no.8, pp.461-466, 2019.

[24] Pokhrel S R, "Towards Efficient and Reliable Federated Learning Using Blockchain For Autonomous Vehicles," *Computer Networks*. 2020 Jul 21:107431.

Sumarga Kumar Sah Tyagi (M'19) is working as an Assistant Professor at Zhongyuan University of Technology, Zhengzhou, China. Dr. Sah Tyagi has received MSc. degree in Computer Science and Ph.D. degree in Wireless Communication from the South Asian University (established by SAARC countries), New Delhi, India, and the Institute of Computing Technology, Chinese Academy of Sciences, Beijing, respectively. His research interests focus on cutting-edge AI enabled Communications and Computing technology. He has published 12+ SCI papers and EI conferences. He serves as Lead Guest Editor for several top-tier journals. He is a recipient of several prestigious scholarships/awards from different governments, including "CAS-TWAS President's Fellowship-2014" for the duration of Ph.D. from government of China and Italy, and "SAARC Silver-Jubilee Scholarship" (2012-2014) from Indian government for the duration of studying Master degree.

Amrit Mukherjee (M'15) obtained a Ph.D. from KIIT University, India, in 2017. He is currently working in School of Electronics and Information Engineering, Anhui University, Hefei, PR China. He was a Post-Doc Research Fellow in School of Computer Science and Communication Engineering, Jiangsu University, PR China from May 2018-June 2020. He has published more than 54 research articles and submitted 4 patents till date. He also served special issue guest editor for Computer Communications, Journal of System Architecture and Computers, Materials and Continua. His area of interests include Artificial Intelligence, Wireless Sensor Networks, Cognitive Radio, IoT and signal processing.

Shiva Raj Pokhrel received the Ph.D. degree in ICT engineering from Swinburne University of Technology, Melbourne,Australia, in 2017. Dr. Pokhrel was the recipient of the Marie Skłodowska Curie Grant Fellowship in 2017. He is currently an Assistant Professor with Deakin University, Geelong, Australia. From 2017 to 2018, he was a Research Fellow with the University of Melbourne, Melbourne, Australia and a Network Engineer with Nepal Telecom, Kathmandu, Nepal, from 2007 to 2014. His current research interests include federated learning, blockchain, and IoT.

Kamal Kant Hiran works as an Assistant Professor, School of Engineering at the Sir Padampat Singhania University (SPSU), Udaipur, Rajasthan, India as well as a Research Fellow at the Aalborg University, Copenhagen, Denmark. He is a Gold Medalist for M. Tech (Hons.). He has experience of 15+ years as an academician and researcher in Asia, Africa and Europe. He is recipient of several awards and recognition from IEEE and Elsevier. He has published 35 research papers in SCI/Scopus/Web of Science Journals, Conferences and 7 books with International Publishers.